Decision Fatigue in Physicians

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A recognized problem in administering medical care is physicians' excessive workload. We explore its behavioral consequences from the perspective of decision fatigue—the decline in decision quality due to an increased number of patients and treatment decisions. We use administrative data from over 250,000 visits to an emergency department to analyze how decision fatigue affects physician decision-making and patient outcomes. Controlling for various confounding factors, we find that every 10 patients the physician had previously treated during a shift lowered the index patient's inpatient admission probability by 10.6%, reduced the number of task orders by 10.3%, and shortened the length of stay by 15.7%. Subsequently, both patient revisit rates and mortality rates increased, by 3.0% and 13.3%, respectively. Furthermore, we find that the observed consequences of physician decision-making can be alleviated by taking a break and by accumulated medical experience. These findings suggest that decision fatigue erodes the quality of physician decision-making and impairs patient outcomes, which have important implications on the long-standing debate regarding regulations for healthcare professionals and excessive physician workload. (JEL D91, I18, J44)

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I. Introduction

Physicians' excessive workload is a long-standing problem in medical care (Dzau et al., 2018). The problem has worsened in recent years, largely driven by public pressure to reduce operating costs and an aging society that generates greater healthcare needs. Physicians in the United States, for example, on average treat 21 patients per day and work 53 hours per week (Physicians Foundation, 2016). Numerous studies have shown that a heavy workload impairs the quality of medical care (Michtalik et al., 2013). For instance, a large portion of medical errors, estimated to cause more than 250,000 deaths each year in the United States, has been attributed to physicians' excessive workload. Rising awareness of the workload problem has spurred public debate regarding restrictions on residents' duty hours (Philibert et al., 2002). While duty-hour restrictions reduce excessive workloads, policy makers are concerned that shorter shifts can potentially cause more inpatient handoffs and work compression (Gee, 2011).

This study examines the relationship between physician workload, physician decision-making, and the quality of administered medical care from a behavioral perspective. Excessive workload for physicians is mostly characterized by an increased number of patients to be treated and, consequently, an increased number of decisions to be made during a shift. One important consequence of excessive workload is decision fatigue, a notion recently proposed by behavioral scientists. More specifically, because decision-making requires mental resources that are in limited supply, decision quality declines after making a sufficiently long series of decisions (Baumeister et al., 1998). For example, the decision quality of consumers, financial analysts, voters, and even judges is negatively affected by the number of decisions they have previously made (Levav et al., 2010; Danziger et al., 2011; Augenblick and Nicholson, 2015; Hirshleifer et al., 2019). Studies have also shown that for every hour later in the day, students are more likely to underperform on standardized tests (Sievertsen et al., 2016) and clinicians to prescribe unnecessary antibiotics (Linder et al., 2014) because of their taxed mental resources. Moreover, as anecdotal evidence suggests, Barack Obama, Steve Jobs, and Mark Zuckerberg, among others, have often adopted a minimalist approach to reduce decision fatigue.[1] In healthcare, an excessive workload compels physicians to make too many medical decisions, which can erode their decision quality and cause often dire consequences for patients. Hence understanding its psychological underpinnings is crucial for reducing overall medical and financial burdens.

We hypothesize that decision fatigue, indexed by the number of patients a physician treats in a given shift, potentially erodes physician decision quality and patient health outcomes. To test this hypothesis, we employ administrative data from a large emergency department (ED) in Singapore. Our dataset contains 254,320 patient visits with 129 physicians over a period of 2 years. This dataset uniquely fits our research objective in four respects. First, the hospital information system documents comprehensive records on all ED visits, including patient characteristics, physician decisions, patient outcomes, and, importantly, timestamps for the patient's path through the ED. Second, financial incentives are unlikely to play a role in the ED we studied, as physicians are paid a monthly salary with a fixed shift allowance, and patients incur a fixed attendance fee upon registration. Third, physicians and patients are generally randomly matched, due to the numerous modalities of cases that present for emergency care combined with physicians' predetermined shift schedules (Chan, 2016, 2018). Last, Singapore's centralized ambulance system ensures that ambulance arrivals at the ED are exogenous to hospital conditions. This exceptional institution serves as a quasi-experiment to identify the causal effect of decision fatigue, since ambulance arrivals contribute to a substantial proportion of physicians' workload.

[1] See "The scientific reason why Barack Obama and Mark Zuckerberg wear the same outfit every day" by Baer Drake (2015) https://www.businessinsider.com/barack-obama-mark-zuckerberg-wear-the-same-outfit-2015-4.

We find a decrease in the probability of inpatient admission, number of task orders, and patient length of stay as the number of patients a physician treats in a given shift increases. Controlling for various confounding factors, ordinary least squares (OLS) estimates suggest that every 10 patients a physician has previously treated during a shift lower the index patient's probability of inpatient admission by 10.6%, reduce the number of task orders by 10.3%, and shorten the length of stay by 15.7%. We further examine the extent to which we can identify the causal effect in two separate analyses. First, we show that these results are robust after we address potential nonrandom patient-physician assignment by using exogenous ambulance arrivals at the ED as an instrumental variable. Second, we find that the consequences of decision fatigue in physician decision-making could be alleviated by taking a break, which is consistent with previous research demonstrating the beneficial effect of breaks on individuals' performance (Danziger et al., 2011; Sievertsen et al., 2016).

We further investigate whether physicians' decision fatigue aggravates patient treatment outcomes. We find that decision fatigue significantly erodes the quality of patient treatment, leading to a higher probability of patient return visits as well as a higher probability of ED mortality. Specifically, our OLS estimates suggest that every 10 patients previously treated during the physician's shift increase the patient's revisit rates and mortality rates by 3% and 13.3%, respectively.

Finally, we study whether physicians' professional experience mitigates the effect of decision fatigue. To do this, we first estimate the decision-fatigue effect for each physician, then regress the individual-specific estimate on physician's characteristics. Our results suggest that medical experience mitigates the effect of decision fatigue for physicians, although the effect diminishes as the physician ages.

Our study contributes to understanding of the consequences of physician workload in several ways. First, the literature on physician workload exclusively focuses on working hours (Linder et al., 2014; Dzau et al., 2018). Our paper is the first to investigate decision fatigue, measured by the number of patients a physician treats in a given shift. Our results remain significant both economically and statistically after we control for cumulative time elapsed in a shift, which supports a net effect of decision fatigue independent of working hours. We thus provide a new perspective on the long-standing problem of physicians' over-workload in medical care. Over-workload means not only the number of hours worked, but also the number of patients treated, or the number of decisions made in a given time period. Second, unlike previous studies on physician workload, our data enable us to identify the causal effect of decision fatigue. We use an instrumental variable (IV) method to examine the causal relationship between decision fatigue and physician decision-making, exploiting the exogeneity of ambulance arrivals at the ED. Third, with patient treatment outcomes available, our study is able to assess whether and how decision fatigue affects the quality of physician decisions. Lastly, physician-level information allows us to examine how physician characteristics—in particular, professional experience—affects physicians' responsiveness to decision fatigue.

Our study also contributes to the increasing literature on the use of behavioral economics to understand medical decision-making and overcome challenges in healthcare (i.e., Wakker, 2008; Cohen et al., 2016; Li et al., 2017). Specifically, overworked physicians are vulnerable to cognitive biases and making suboptimal decisions (Chandra et al., 2011). Our study evaluates the effect of physicians' excessive workload from the perspective of decision fatigue, which has been shown to affect the decision quality of consumers, financial analysts, voters, and even judges (Levav et al., 2010; Danziger et al., 2011; Augenblick and Nicholson, 2015; Hirshleifer et al., 2019). The psychological mechanisms that underpin decision fatigue can perhaps be best understood within the framework of two systems of cognitive processes (Kahneman, 2011). In this scheme, decisions arise from either the fast and effortless System 1 or the slow and effortful System 2. As physicians suffer from increasingly depleted mental resources toward the end of their shift, they must rely more on System 1 to make fast and effortless decisions. Hence, they are more likely to make poorer decisions that lead to worse patient outcomes. Relatedly, our results are also consistent with recent literature on the behavioral consequences of scarcity (Shah et al., 2012; Mani et al., 2013; Shafir and Mullainathan, 2013). These studies argue that resource scarcity impedes cognitive function, which in turn may lead to suboptimal decisions. In our context, an increased number of patients may generate a sense of scarcity in terms of cognitive resources, which leads to physicians' diminishing performance.

Our study further contributes to a growing literature on health economics that analyzes physician decision-making. It is well documented that physicians' performance is determined not only by their human capital (Currie and MacLeod, 2017), but also by their surrounding environments (Chandra and Staiger, 2007; Chan, 2016). The latter includes extraneous factors unrelated to patients' health. For instance, financial and liability considerations may sway physicians to perform unnecessary procedures (Currie and MacLeod, 2008; Clemens and Gottlieb, 2014). A recent study by Fang and Gong (2017) finds that physicians' financial incentives also affect their decisions on Medicare claims. Closely related to our study is the work of Chan (2018), who examines two behavioral distortions in ED physicians due to work schedule. First, physicians accept fewer patients near end of shift. Second, physicians shorten the duration of care and increase formal utilization on patients assigned near end of shift. Our study contributes to understanding of how physicians make sequential decisions over the course of a shift.

The rest of the paper is organized as follows. Section 2 describes the institutional background and the dataset. In Section 3 and Section 4, we estimate the effects of decision fatigue on physician behavior and patient health outcomes, respectively. In Section 5, we examine whether professional experience mitigates the effect of decision fatigue. Section 6 concludes with a discussion of policy implications.

II. Institutional Setting and Administrative Data

In this section we describe the institutional background, introduce the administrative data, construct patient flow and physician shifts, and define main variables.

A. Institutional Setting for Identification

A key challenge in identifying the effect of decision fatigue on physician decision-making is the endogenous matching between patients and physicians. In most healthcare settings, patients are not randomly assigned to physicians: Not only do patients search for physicians, but physicians also select their patients. By contrast, our research setting of the ED offers three distinct advantages to address this challenge.

Patients and physicians are almost randomly matched in the ED (Chan, 2016, 2018). The rationale is twofold. First, ED visits are unplanned. Patients are not likely to select their physicians due to the unexpected nature of emergency care, and upon arrival they are assigned by a triage nurse to on-shift physicians. Second, the internal shift scheduling of physicians is predetermined, and physicians cannot control the volume of ED arrivals or the types of patients assigned to them by the triage nurse. As a result, the match between patients and physicians is largely random.

In addition, the ambulance system is centralized in our setting, which ensures that ambulance arrivals at the ED are exogenous to hospital conditions. Singapore's emergency medical services system is operated by the Singapore

Civil Defense Force (SCDF). Table A1 shows that SCDF ambulances transport more than 93% of the ambulance arrivals in our data. SCDF ambulance personnel convey patients only to the nearest hospital, and will not consider requests to redirect patients to alternative hospitals. As a result, the number of ambulance arrivals at the ED should be independent of hospital characteristics. At the same time, patients who arrive by ambulance are a major determinant of physicians' workload in the ED. This unique institutional feature allows us to identify the causal effects of decision fatigue using the quasi-experimental variation in physicians' workload induced by ambulance arrivals.

Finally, physicians' decisions in the ED we study are not influenced by financial incentives. Government subsidies are provided for every ED patient regardless of nationality, and all patients incur a fixed attendance fee upon registration. Physicians are paid a basic monthly salary with a fixed shift allowance, and are compensated based on neither the quality nor quantity of work during the scheduled shift.

B. Administrative Data

We obtain administrative data for all patient visits to a large ED in Singapore from January 1, 2011, through December 31, 2012. The hospital information system documents comprehensive records for each visit, including patient characteristics, physician identifier, clinical decisions, patient outcomes, and, importantly, timestamps for the patient's path through the ED. These records allow us to track real-time patient flow and the universe of physicians' activities in the ED.

Over the 2 years, we observe 264,115 raw patient visits to the ED. We construct real-time patient flow volume and physician shift schedules using all visits. For the purpose of analysis, we limit our attention to physicians who treat a minimum of 100 patients during the sample period and shifts with duration between 3 and 24 hours.[2] We also exclude visits in which the patient died upon arrival, left before being seen, or discharged against medical advice. Our final sample contains 254,320 patient visits with treatment by 129 physicians.

Patient Flow.—Figure A1 illustrates the patient flow process in the ED. Upon arrival at the ED, patients are registered, screened, and triaged by a triage nurse. Triage is based on a three-level patient acuity category scale (PACS), with level 1 being the most severe cases, level 2 major emergencies, and level 3 minor emergencies (henceforth non-severe cases). A scheduling system then determines the assignment of patients to each on-shift physician and the order of their consultations on a first-come, first-served basis. Patients with severe conditions (PACS levels 1 and 2; henceforth severe cases) have higher priority. A few patients leave after the initial consultation, but most undergo some type of diagnostic testing such as lab work or X-rays, or receive treatment by a nurse or physician assistant. When test results are available or the treatment is completed, the patient is reviewed by the same physician before being discharged or hospitalized.

The administrative dataset records real-time patient flow in the ED. It is organized by patient visits, with each record corresponding to a single visit. Each record contains detailed timestamps for the patient's complete path through the ED, such as when a patient arrived at the ED, when the patient was seen by a physician, when the physician ordered any test or treatment, and when the physician made a final discharge disposition. For each visit, the physician who carried out patient care is identified by a unique ID. Since the dataset records information on clinical workflow for all visits, we are able to track the universe of physicians' activities in the ED.

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[2] In the robustness analysis, we restrict shift length to be between either 6 and 12 hours or 8 and 10 hours.

Physician Shifts.—Following the procedure of Brachet et al. (2012), we construct physicians' shifts based on their periods of inactivity, which is identified by their absence from the administrative data. Sorting data first by physician ID, then by the date and time during which physicians were involved in each patient visit, we define the beginning of a new shift when 6 or more hours have elapsed between consecutive observations of the same physician. The rationale behind the 6-hour cutoff between visits to define a new shift is as follows. First, it is almost impossible for a physician to be on duty for 6 consecutive hours without a single case, given overcrowding and long waits in the ED. Second, a physician's rest period between two consecutive shifts is unlikely to be less than 6 hours.

The shifts we identified from the data may differ from actual shift schedules. For example, if on-duty physicians remain inactive for 6 or more hours, our procedure will assign them a new shift, even though they could still be on the same long shift. However, this type of misclassification does not pose any threat to the validity of our estimates. The effect we aspire to identify arises from the decision fatigue that results from making repeated patient care decisions, rather than long on-duty hours. A physician may be well rested after long hours that did not include patient care, in which case it is reasonable to define a new shift for the purposes of our study. In another example, if the rest between two consecutive shifts is less than 6 hours, we classify the physician as being on a longer shift. We also use 4-hour and 5-hour cutoffs to define new shifts as robustness checks. The results presented below are not sensitive to these alternative definitions.

Once the shifts are defined, we measure the duration of a shift as the number of hours elapsed from the start of the first patient's consultation to the end of the last consultation in the shift. Figure A2 plots the distribution of shift durations. The most frequently occurring duration is around 8 hours, and half of the shifts are longer than 8 hours. The actual hours worked may differ from planned work schedules, as ED physicians may have unpredictable work schedules for unforeseen circumstances. For example, physicians are expected to work beyond scheduled shifts for reasons such as task completion and staffing shortages (Morrow et al., 2014).

C. Main Variables and Summary Statistics

Decision Fatigue.—During our study period, physicians on average treat 21 patients per shift and work 42 hours per week in the ED. These physicians' workloads are comparable to those observed in the literature on excessive physician workload (Physicians Foundation, 2016). Different from the literature that measures physicians' over-workload by long working hours, we characterize excessive workload based on the number of decisions, such as task orders and treatment decisions. Previous studies in decision science and behavioral economics suggest that making sequential decisions depletes individuals' executive functioning and causes mental fatigue, which can influence subsequent decisions (Levav et al., 2010; Danziger et al., 2011; Augenblick and Nicholson, 2015; Hirshleifer et al., 2019). We measure decision fatigue as the number of patients the physician treats in a given shift. This ordinal position serves as a proxy for the real-time cumulative workload and a measure of the physician's cognitive depletion. As shown in Panel A of Table 1, on average, a physician has treated 10.3 patients before the index patient's consultation in a given shift.

Physician Decisions.—We have three measures for physician decisions: (i) inpatient admission, (ii) number of task orders, and (iii) patient length of stay. Panel B of Table 1 presents summary statistics for these three decision variables.

Physician's discharge decision is the primary product of ED care and a matter of discretion for physicians (Chan, 2018). After the completion of diagnosis and treatment, the physician may discharge a patient to home or refer him or her to a primary care center for follow-ups. If a patient has a serious condition, the physician may admit the patient to receive inpatient treatment. The admission disposition does not necessarily mean the end of ED care, as inter-unit handoffs from the ED to inpatient care require coordination between different parties. Patients awaiting inpatient admission may have to remain in the ED for at least several hours. We focus on the decision to admit the patient for inpatient care as a key outcome measure, which accounts for 21.6% of sample visits.

We also examine physician input of care for task orders and consultation time. Medical task orders include treatments, procedures, tests, and medications. We count the total number of task orders to measure hospital resource utilization. We measure the length of stay as the minutes elapsed from the start to the end of the patient's consultation with the specific physician.[3] As shown in Panel B of Table 1, on average, a patient receives 6.2 tasks and stays for approximately 1 hour in the ED.

Patient Outcomes.—We focus on two measures of patient health outcomes: ED revisits and mortality.[4] ED revisits measure whether a patient revisited the same ED within 1 week.[5] ED mortality indicates whether a patient died in the ED after being assigned to a physician. Panel C of Table 1 reports summary statistics for these two variables. The 7-day revisit rate is 8.4% and the ED mortality rate is 0.3%.

Patient Characteristics.—We observe much of the information available to the physician at the time of accepting the patient, including the patient's gender, race,

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[3] This time duration includes the time for history-taking, initial examination, formal tasks, and review of test results, but excludes waiting times for initial consultation and admission to an inpatient ward.

[4] Since our data are confined to what happens within the specific ED, we are only able to use these two variables to measure patient health outcomes.

[5] We identify multiple visits for the same patient using comprehensive patient information that includes gender, race, birthdate, and home address.

age, and triage severity level. Panel D of Table 1 reports summary statistics for these ex ante patient characteristics. In our data, 65% of the patients who visited the ED during the sample period are men. The average age of patients is around 39 years. Seventy-two percent of patient visits are minor emergency cases; the remaining 4% are PACS level 1 cases, and 24% are level 2.

We also have diagnostic information for each patient. This information is only incompletely known by physicians prior to consultation via the patient's chief complaint. Formal diagnostic judgments are made after physicians interact with patients or review their test results. We codify the diagnostic information into 19 broad categories based on the International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM).[6]

Patient arrivals at the ED are not smooth; we observe considerable fluctuations in ED occupancy over time. For example, Sunday and Monday are the busiest days within a week, and 10 am to 3 pm and 8 pm to 11 pm are the two peak hours within a day. The total number of patient visits increased over the 2 years, and ED patient volumes varied across months. We include a set of time fixed effects in our regression analysis to account for time variations.

Physician Characteristics.—To test the relationship between experience and physicians' responsiveness to decision fatigue, we obtained a sample of 115 physicians out of the 129 physicians with non-missing information on physician characteristics, which include age, gender, educational background, and medical experience. Medical experience is defined as the number of years since a physician obtained his or her first degree to practice medicine. To capture training

[6] Diseases are classified into 19 broad categories: infectious and parasitic diseases, neoplasms, endocrine-nutritional-metabolic diseases, diseases of the blood, mental disorders, diseases of the nervous and sense system, diseases of the circulatory system, diseases of the respiratory system, diseases of the digestive system, diseases of the genitourinary system, complications of pregnancy and childbirth, diseases of the skin and subcutaneous tissue, diseases of the musculoskeletal system, congenital anomalies, disorders originating in the perinatal period, signs-symptoms, injury-poisoning, external causes of injury, and supplementary classification.

background, we include a dummy variable indicating whether a physician obtained the first medical degree from a local university or from an overseas university. Compared with graduates abroad, physicians trained at home may have better knowledge of local demographics and institutional regulations. We also measure whether the physician received continuing medical education after completing the initial medical education. Continuing medical education is defined as the acquisition of professional medical credentials after the initial graduation from medical school.

Panel E of Table 1 presents summary statistics for physician characteristics. On average, a physician has been in practice for 8 years since obtaining the first medical degree. The majority of ED physicians are male (79.1%). Around half (53.9%) obtained their initial medical training locally, and more than one-quarter (27.8%) obtained additional medical credentials after their initial medical education.

III. Impacts of Decision Fatigue on Physician Behavior

In this section we conduct regression analyses to quantify the effect of decision fatigue on physician behavior, controlling for patient demographics, case severity, diagnostic categories, physician fixed effects, and a series of time fixed effects. We then examine whether and how taking a break alleviates the consequences of decision fatigue. To address concerns regarding potential nonrandom patient assignment, we also explore a unique institutional feature to establish the causal link between decision fatigue and physician decisions. We further assess the robustness of our results by performing an extensive array of sensitivity analyses. Finally, we explore the heterogeneous effects of decision fatigue on physician behavior to investigate the mechanism.

A. Baseline Regressions

Panels A-C in Figure 1 plot physician decisions by the number of patients previously treated within the shift based on the raw data. In Panel A, we observe a monotonic and dramatic decline in the likelihood of inpatient admission as the number of patients treated by the physician increases. Panels B and C show that physicians reduce task orders and shorten patient length of stay after they have treated more patients in a shift. To rigorously examine the graphical pattern, we conduct regression analyses controlling for multiple confounding factors.

Regression Specification.—We start from a linear model in which we assume that, conditional on patient characteristics, physician fixed effects, and time fixed effects, neither patients nor triage nurses select physicians in the ED; instead, patient visits are randomly assigned to each on-shift physician. The baseline regression that describes the association between decision fatigue and physician behavior is:

(1) $$Y_{ijt} = \alpha PatientCount_{ijt} + X_i\beta + \nu_j + T_t + \epsilon_{ijt},$$

where medical decision $\mathrm{Y_{ijt}}$ is indexed for patient visit *i* treated by physician *j* starting consultation at time *t*. For the inpatient admission decision, $\mathrm{Y_{ijt}}$ is a dummy variable that equals one if patient *i* is admitted to inpatient care and zero otherwise. For the measure of task orders, $\mathrm{Y_{ijt}}$ represents the total number of task orders for patient *i*. For patient length of stay, $\mathrm{Y_{ijt}}$ takes log transformation. We fit linear models for all outcomes, and conduct an additional probit regression for the binary variable of inpatient admission decision.

Our independent variable of interest is physician decision fatigue, $PatientCount_{ijt}$, which counts the number of patients seen by physician *j* during the shift before start time t of patient *i*'s consultation. $\mathrm{X_i}$ is a vector of the index patient's characteristics, including patient demographics (age, gender, and race), triage severity levels, and diagnostic categories.[7] We also control for physician fixed effects ν_j and time fixed effects T_t. Time fixed effects include hour of day, day of week, and month-year interactions. The error term, ϵ_{ijt}, captures measurement errors. We cluster standard errors at the physician level.

Regression Results.—Panel A of Table 2 shows the estimation results from Equation (1). We are interested in the estimate of α, which measures the effect of decision fatigue on physician behavior. Across all columns, the estimates are statistically significant and negative, suggesting that the declining patterns in the left panels of Figure 1 hold after controlling for patient demographics, case severity, diagnostic category, physician fixed effects, and time fixed effects.[8]

Columns (1) and (2) present results for inpatient admission. The OLS estimate of α in Column (1) is -0.0023 (standard error 0.0003). This estimate suggests that every 10 patients the physician has previously treated during the shift lower the index patient's inpatient admission probability by 10.6%.[9] The average marginal effect from the probit estimation is -0.0029 (standard error 0.0004), as shown in Column (2). No significant difference exists between the OLS estimate and the marginal effect from the probit model. Henceforth, we only discuss OLS estimates.

Columns (3) and (4) show estimates for decision-fatigue effects on task orders and length of stay. Physicians tend to reduce task orders and shorten patient consultation time as they advance in the sequence of patient visits. Patients

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[7] Diagnostic categories might be endogenous in Equation (1), as they are partly determined by patient care and physician diagnostic performance. Our main results are essentially unchanged in the robustness analysis that excludes diagnostic categories (Table A.2).

[8] To save space, we only report estimates for the key coefficient, i.e., α. Estimates for coefficients on other control variables have expected signs and magnitudes. Full results are available upon request.

[9] 0.106=0.0023*10/0.216, where 0.216 is the mean inpatient admission rate in our data.

receive 0.633 fewer orders if the physician has previously treated 10 more patients in the shift, which translates into a 10.3% reduction given the sample mean of 6.152 orders. Meanwhile, patient length of stay is shortened by 15.7% for every 10 additional patients previously treated by the physician during the shift.

These results suggest that decision fatigue plays a significant role in physician decision-making. When physicians are mentally fatigued, they tend to simplify medical decisions by lowering inpatient admissions, reducing task orders, and shortening the length of stay. Two facts support our view that inpatient admission is a more complex decision than outpatient discharge, and thus a less likely outcome when decision fatigue increases. First, the physician must decide which specialist department is the most appropriate to admit the patient to for further treatment. This is not a straightforward decision, especially for patients with multiple medical problems. Second, the physician must coordinate with the specialist department for inter-unit handoffs. After approval of the admission request, the patient remains in the ED until an inpatient bed becomes available.

B. Breaks within a Shift

It has been suggested that mental fatigue and its related consequences can be partially overcome by a short rest (Danziger et al., 2011). Using the administrative data, we define a break as a period of at least 30 minutes, during which the physician on shift is not in charge of any patient.[10] The break divides a shift into distinct decision sessions. Here we restrict our analytic sample to patient visits with physicians who are working in a shift with one break. This restriction yields a working sample of 63,089 visits.

[10] Our result remains robust if we define a break as a period of at least 60 minutes of being inactive.

Panels D-F of Figure 1 plot physician decisions by the number of patients treated in each session, and demonstrate that the break restores the physician to a high level of functioning. Panel D shows that the probability of inpatient admission steadily declines as the number of previously treated patients increases, but rebounds right after a break. Similarly, Panels E and F show that the number of task orders is larger, and the length of stay is longer at the very beginning of each session than later in the session.

To rigorously examine the graphical pattern above, we extract three groups of patient visits from the analytic sample. Group 1 comprises the last fourth to sixth patient visits treated before the break, Group 2 the last three visits before the break, and Group 3 the first three visits after the break. Using these patient visits, we estimate the following equation:

(2) $$Y_{ijt} = \alpha_1 Group1_{ijt} + \alpha_2 Group3_{ijt} + X_i\beta + \nu_j + T_t + \epsilon_{ijt},$$

where $\mathrm{Group1}_{\mathrm{ijt}}$ and $\mathrm{Group3}_{\mathrm{ijt}}$ are dummy variables indicating whether patient visit i belongs to Group 1 or Group 3, respectively. The omitted reference category includes patient visits in Group 2. Other variables are defined similarly to Equation (1). Standard errors are clustered at the physician level.

Holding other variables constant, α_1 measures the difference in physician decisions between Group 1 and Group 2 patient visits. On average, Group 2 visits have three more previously treated patients in a shift than Group 1 visits. So $-\alpha_1$ represents the effect on physician decisions when the number of previously treated patients increases by three in a shift. α_2 measures the difference in physician decisions between Group 3 and Group 2 patient visits. On average, the number of previously treated patients in a shift increases by three comparing Group 3 visits with Group 2 visits. Moreover, a break occurs between Group 2 and Group 3 visits. Thus, α_2 represents the combined effect of treating three more patients in a shift and taking a break during the shift. As a result, the effect of a break is captured by $\alpha_1 + \alpha_2$ (i.e., $\alpha_2 - (-\alpha_1)$).

Table 3 shows the estimation results from Equation (2). OLS estimates for α_1 and α_2, with only one exception, are statistically significant and positive. This result confirms the pattern depicted in Panels D-F of Figure 1—namely, the declining trend within a session and the restoration right after a break. Moreover, the effect of a break, $\alpha_1 + \alpha_2$, is estimated to be statistically significant and positive in all columns. This result is consistent with findings in the literature that mental resources can be replenished by interventions such as a short rest (Danziger et al., 2011; Sievertsen et al., 2016).

C. Consideration of Nonrandom Work Assignment

The assignment of patients to physicians may not be random, which is a major concern for interpreting the association between decision fatigue and physician behavior embodied in Equation (1). Although the ED provides a context in which patients and physicians are nearly randomly matched, the challenge to causal inference based on OLS estimates remains. For example, triage nurses may observe the degree of physicians' decision fatigue and assign fewer complicated cases to more fatigued physicians. If this were the case, our OLS estimates would be biased.

We address this concern by exploring a unique feature of Singapore's centralized emergency ambulance system. As described in the previous section, the number of ambulance arrivals strongly predicts the volume of work in the ED, but is orthogonal to hospital conditions. Therefore, we use the total number of ambulance arrivals at the ED during the physician's shift up to the arrival of the index patient as an IV for the number of patients previously treated by the physician. Panel F of Table 1 shows that on average, 10 patients arrived at the ED by ambulance from the physician's shift start to the index patient's consultation. Panel B of Table 2 reports first-stage results, showing a strongly positive correlation between the number of ambulance arrivals and a physician's workload. The estimates are statistically significant, with t-statistics being around 23, suggesting that the weak instrument problem is less of a concern in our study.

Panel C shows that the signs of IV estimates are consistent with OLS estimates, but their magnitudes are substantially larger. Specifically, every 10 patients previously treated cause the on-shift physician to lower the probability of inpatient admission for the index patient by 14.8%, reduce the number of task orders by 15.3%, and shorten the length of stay by 19.6%. Results of the Hausman test show that the differences between OLS and IV estimates are statistically significant at the 1% level. This suggests that OLS estimates are biased downward, perhaps because triage nurses take into account physicians' decision fatigue when assigning patients to physicians. However, the effect of decision fatigue on physicians remains substantial, as the sizable OLS estimates suggest. Triage nurses' strategic assignments cannot completely remove the decision-fatigue effect on physician behavior.

D. Robustness Checks

Table 4 presents a number of robustness checks. We consider the possible roles of physician physical fatigue, multitasking, the end-of-shift effect, and ED crowdedness, which may confound our main estimates. We also conduct subsample analysis by patient severity and physician shift length. Our results remain robust in these analyses.

Decision Fatigue vs. Physical Fatigue.—Physicians can be mentally and physically fatigued at the same time. Physical fatigue, often caused by long working hours and hard physical labor, can negatively impact performance at work. Our measure of decision fatigue—the number of patients previously treated in the shift—is correlated with elapsed time in a given shift. That is, physicians treat more patients as the shift wears on. One might thus be concerned that the decision fatigue effect we identify is due to working hours rather than decision fatigue per se; physicians could behave differently due to longer working hours. To address this concern, we conduct a regression analysis that includes cumulative hours elapsed in the physician's shift as an additional control variable.

Panel A of Table 4 reports regression results after controlling for cumulative time. Coefficients on the number of patients previously treated remain negative and statistically significant in all models, although the magnitudes are smaller than those in baseline regressions. This result suggests that the observed behavioral response of physicians to decision fatigue does not reflect only the effect of elapsed working time. For a given working period, repeated decision-making exhibits a statistically and economically significant effect on physicians' subsequent decisions. In particular, this interpretation should be viewed in light of the high correlation between the number of patients treated and cumulative hours (Pearson correlation=0.67, p<0.001).

Physicians' Multitasking.—ED physicians attend to multiple patients at the same time due to the increased demand for emergency services. An emerging literature in experimental psychology and cognitive neuroscience has demonstrated that multitasking impairs workers' decision-making and decreases productivity (Hallowell, 2005). In healthcare operations, a recent work by KC (2014) shows that excessive multitasking by ED physicians adversely impacts productivity and the quality of care. We are concerned that physicians may multitask to a higher degree as their shift wears on, which would bias our baseline estimates.

Given this concern, we consider physicians' multitasking in a robustness check. We define multitasking as the number of patients concurrently managed by the physician during the index patient's consultation. Panel B shows that our main results remain largely unchanged after controlling for the level of physician multitasking.

End-of-shift Effect.—Previous studies have provided evidence on performance deterioration near the end of workers' shifts (Brachet et al., 2012; Chan, 2018). For example, Chan (2018) finds that ED physicians order more formal tasks and complete their work earlier as the end of the shift approaches. The number of previously treated patients, and thus our measure of decision fatigue, is larger at the end of each shift than anywhere else in the shift. To check whether our estimates of a decision-fatigue effect are driven by end-of-shift effects, we exclude the last three patient visits in each shift from the robustness analysis.

Panel C presents regression results for this restricted sample. Estimates remain almost the same as those in our main analyses. The observed effect of decision fatigue on physician decisions cannot be attributed to the end-of-shift effect.

ED Crowding.—Another potential confounding factor in estimating the decision fatigue effect is ED crowding. For instance, physicians may continuously monitor ED queue status through a computer terminal. Studies have found that overcrowding in the ED influences not only discharge decisions, but also test ordering and patients' length of stay (Freeman et al., 2017; Chiu et al., 2018). ED crowding also results in an increased workload, and thus correlates directly with our measure of decision fatigue. To address this concern, we conduct a robustness analysis that controls for ED crowding.

We have two measures for the degree of crowding in the ED. The first is the total number of patients waiting to be seen in the ED at the time of the index patient’s consultation starting. The second is the physician-adjusted value of system load, defined as the ED system load divided by the total number of physicians on staff during the index patient’s consult. ED system load measures the total number of patients in the ED, including those waiting to be seen and those being treated.

Panels D and E present estimated coefficients after controlling for the total number of patients in the waiting area and the adjusted system load, respectively. Regardless of which measure is used, the estimates on decision fatigue are essentially the same as those in our baseline estimation. ED crowdedness thus cannot explain the observed effect of decision fatigue on physician behavior.

Severe vs. Nonsevere Current Cases.—To investigate whether the baseline finding holds for patients of different severity levels, we estimate Equation (1) separately for severe and nonsevere cases. Panels F and G show that OLS estimates remain statistically significant and negative for both groups. Physicians reduce the probability of inpatient admission, issue fewer task orders, and shorten patient length of stay as they treat more patients during a shift.

Restrictions on Physician Shift Length.—We examine the robustness of our results with respect to restrictions on physician shift length. We restrict shift duration to be between 6 and 12 hours, and further to between 8 and 10 hours. Estimates for both subsamples, shown in Panels H and I, are statistically significant and negative. They are similar in magnitude to those in Panel A of Table 2.

E. Heterogeneity Analysis

To better understand the mechanisms underlying the observed behavioral pattern, this section investigates the heterogeneity of the decision-fatigue effect with respect to (i) the severity of previous cases, (ii) rest periods between work shifts, and (iii) gender and race concordance between patient and physician. We also estimate a nonlinear effect of decision fatigue on physician behavior.

Severity of Previous Cases.—The total number of patients previously treated is used as a measure of physician's decision fatigue in the previous analyses. However, the composition of previously treated patients matters when we study the decision-fatigue effect. Treating 10 patients with complex or severe conditions would be quite different from treating 10 patients with mild illnesses. Physicians need more mental resources to treat more severe cases, and thus they suffer from a higher degree of decision fatigue.

To examine the heterogeneous effects by the composition of previously treated patients, we regress physician decisions on both the total number of patients previously treated and the number of severe cases treated. Panel A of Table 5 reports the estimation results. The estimated coefficients for these two variables are statistically significant and negative across all columns. Controlling for the total number of patients treated, an increase in the number of severe cases increases the effect of decision fatigue. This result is consistent with findings in the literature that cognitive depletion is affected by not only the number of decisions, but also the complexity of each decision a decision maker has made (Levav et al., 2010). Severe cases are, on average, more complicated than nonsevere cases, and thus lead to a higher degree of decision fatigue for physicians.

Rest Periods Between Shifts.—A short rest period before starting a new shift may increase the risk of shift work disorder. We examine whether quick returns between shifts exacerbate physicians' decision fatigue. Following the literature, we define a quick return as a dummy variable indicating whether the rest period before starting the current shift is less than 11 hours (Flo et al., 2014). We include the quick return indicator and its interaction with the total number of patients previously treated in Equation (1).

Panel B of Table 5 reports the results. Coefficients on the interaction term are statistically significant and negative in Columns (1) and (2), though insignificant in Column (3). This result suggests that the effect of decision fatigue is larger for physicians who take a shorter time off between work shifts. Our finding is consistent with findings in the literature that quick returns impede mental work ability (Flo et al., 2014).

Patient-physician Race and Gender Concordance.—Concordance by race or gender in patient-physician relationships is associated with more productive communication, better exchange of health information, and greater patient satisfaction (Cooper-Patrick et al., 1999). We next examine whether patient-physician race or gender concordance alleviates the effect of decision fatigue. We define patient-physician race (gender) concordance as a dummy variable indicating whether the index patient and physician share the same race (gender). We add the two dummy variables and their respective interactions with the number of patients previously treated to Equation (1).

Panel C shows that decision fatigue has a smaller effect on physician decisions when patients share the same race or gender as the physician. In particular, Column (1) suggests that the reduction in the probability of inpatient admission caused by increased decision fatigue is smaller when the index patient shares the same gender as the physician. Column (2) shows that the reduction in the number of task orders induced by decision fatigue is alleviated by race and gender concordance between patients and physicians.

Our findings could be driven by two channels. Physicians may have better knowledge of their race (gender) concordant patients than of race (gender) discordant patients. Also, shared identities facilitate effective communication between patients and physicians. Both channels suggest that physicians could put less mental effort into gathering diagnostic information and making clinical decisions for their race (gender) concordant patients. Consequently, decision fatigue has a smaller effect on physicians when they share the same race or gender as their patient.

Nonlinear Decision-fatigue Effect.—The effect of decision fatigue on physician behavior might not be linear. To investigate this possibility, we estimate Equation (1) by replacing the number of patients previously treated by the physician with a series of dummy variables to indicate the ordinal position of the index patient visit within a shift. Specifically, we categorize patient visits into eight groups. The first group includes visits whose consultation starts when the physician has previously treated 0 to 2 patients during the shift. The second group includes visits treated after 3 to 5 patients, the third 6 to 8, and so on through 18 to 20, with a final group of more than 20. The estimation equation becomes:

(3) $$Y_{ijt} = \sum_m \alpha_m D_{ijm} + X_i\beta + \nu_j + T_t + \epsilon_{ijt},$$

where D_{ijm} is a dummy variable indicating that the number of patients seen by physician j before patient i's consultation falls into group m ($m \in \{1, 2, 3, 4, 5, 6, 7\}$). The eighth group, for visits whose consultation starts after the physician has treated more than 20 patients during the shift, serves as the reference category. We cluster standard errors at the physician level.

Table 6 shows estimation results from Equation (3), and Figure 2 plots the estimated coefficients. OLS estimates for α_m's remain statistically significant and positive for most models. We observe a nonlinear effect of decision fatigue, as the estimates decrease in magnitude when the grouping number increases. We note that the reduction is sharper and more pronounced in the earlier part of a shift than in the later part. This result rules out the possibility that physicians speed up only as they approach the end of a shift. Although the effect is more significant in the earlier part of a shift, we note that it persists throughout a shift. This finding rules out the possibility that our estimated effect of decision fatigue might be driven by cases with complicated conditions—which are not captured by triage severity levels or diagnostic categories—at the beginning of the shift.

Discussion of the Mechanism.—Our extensive array of analyses provides consistent evidence that an increased number of patients decreases the probability of inpatient admission, number of task orders, and patient length of stay. The effect is more pronounced if the previously treated patients include a larger proportion of severe cases, or the physician has a short rest before the current shift. By contrast, the effect is smaller when the index patient shares the same race or gender as the physician. Finally, the decision-fatigue effect persists throughout the shift.

These results are broadly consistent with the decision-fatigue interpretation put forward earlier. An increased number of severe cases costs more mental resources of physicians, and thus leads to a larger decision-fatigue effect. Also, a short period of rest cannot fully restore mental resources after an exhausting work shift. The finding that decision fatigue has a smaller effect when physicians treat concordant patients is also consistent with our interpretation: The mental effort of collecting information and making clinical decisions is lower when physician and patient share status similarities. Finally, decision-making in a work shift depletes mental resources continuously, resulting in the persistency of the effect throughout a shift. We therefore conclude that decision fatigue explains our findings that an increased number of patients reduces the probability of inpatient admission, number of task orders, and patient length of stay.

IV. Impact of Physician Decision Fatigue on Patient Outcomes

As demonstrated in the section above, we find that decision fatigue affects physician behavior. In this section we examine the impact of physician decision fatigue on patient health outcomes, which may reflect physician decision quality. As discussed in Section II, we focus on two patient outcomes: whether a patient revisited the same ED within one week and whether the patient died in the ED after arrival.

For purposes of illustration, we stratify patient visits into two groups based on their ordinal sequence in the shift. The first group comprises patients treated in the first half of a shift and the second group the remaining patients in the shift. Figure 3 compares ED revisit rates and mortality rates for these two groups. We find that patients who arrive later in the shift have a higher probability of ED revisits and a higher probability of death. Specifically, the revisit rate increases from 8.3% for the first group to 8.7% for the second group, and the mortality rate from 0.2% to 0.3%. These differences are statistically significant at the 1% level for both outcomes.

To rigorously examine the impact of physician decision fatigue on patient health outcomes, we conduct regression analyses that control for patient characteristics, physician fixed effects, and a series of time fixed effects. The regression specification is similar to Equation (1), but uses different dependent variables. For patient revisits, the outcome variable is a dummy variable that equals one if the index patient revisited the ED within 1 week and zero otherwise. For mortality, the outcome variable is a dummy variable that equals one if the patient died in the ED after arrival and zero otherwise.

Panel A of Table 7 presents OLS estimates for the effect of physician decision fatigue on patient outcomes. Physician decision fatigue has statistically significant and positive effects on both 7-day revisits to the ED and mortality in the ED.

Column (1) of Panel A shows that every 10 patients the physician has previously treated during a shift increase the probability of the index patient's revisit to the ED by 0.25 percentage point, which translates into a 3% increase given the sample mean of 0.084. Column (2) suggests that every 10 patients previously treated are associated with a 0.04-percentage-point (or 13.3%) increase in the probability of death in the ED.

We also conduct IV estimations using ambulance arrivals at the ED as the IV, the same as in Section III.C. Panels B and C present first-stage results and IV estimates, respectively. Consistent with OLS estimates, IV estimates are positive, suggesting that both the ED revisit rate and mortality rate increase with physician decision fatigue. Column (1) shows no significant difference between IV and OLS estimates for the outcome variable of ED revisits (point estimates, 0.00023 vs 0.00025; Hausman test, p=0.907). For the dependent variable of ED mortality, Column (2) shows that the IV estimate is much larger than the OLS estimate (point estimates, 0.00017 vs 0.00004; Hausman test, p=0.004).[11]

To sum up, our results suggest that decision fatigue may erode physician decision quality, which leads to higher ED revisit rates and mortality rates. As the cost of the physician decision fatigue effect on mortality is difficult to monetize, we estimate the extra medical expenditure on ED revisits. Based on our data, we estimate that the average medical expenditure per revisit is SGD 300 (1 USD= 1.35 SGD).[12] If all patients had been treated by a physician who had previously seen 10 more patients in the shift, medical expenditure for the single ED in our setting would have increased by SGD 100,000 per year.

[11] The significant difference between OLS and IV estimates in Column (2) should be interpreted with caution in light of the rare occurrence of ED mortality.

[12] In Singapore, emergency services are subsidized by the government at 50%. Patients pay at least a flat attendance fee of around SGD 120 per visit, which covers basic investigations, procedures, drugs and x-ray services. Charges for other investigations such as CT scans and MRI scans, if they are required, are additional.

V. Medical Experience and Decision Fatigue

Results in the sections above indicate that decision fatigue affects physician decisions and has a negative effect on patient health. The literature suggests that increased experience may reduce cognitive workload or cognitive bias (List, 2013). Here we examine whether and how medical experience mitigates the effect of decision fatigue on physician decision-making.

We first estimate the decision-fatigue effect for each physician and subsequently regress this physician-specific estimate on physician's characteristics. The equation that characterizes the relationship between physician-specific decision-fatigue effects and medical experience is:

$$\text{(4)} \qquad \alpha_{Yj} = \beta_0 + \beta_1\, exp_j + \beta_2\, exp_j^2 + X_j\gamma + \epsilon_{Yj},$$

where the dependent variable, α_{Yj}, is the OLS or IV estimate of the physician-specific decision-fatigue effect on decision Y for physician j.[13] The independent variable of interest, exp_j, measures years of medical experience for physician j. We use a quadratic model to fit the relationship between decision-fatigue effects and medical experience conditional on covariates $\mathrm{X_j}$. The covariate vector $\mathrm{X_j}$ represents additional characteristics of physician j, including gender, one dummy variable that indicates a first degree from a local medical school, and another dummy variable that indicates continuing medical education. ϵ_{Yj} is the error term. As the dependent variable in Equation (4) is the estimate from Equation (1), we bootstrap the standard errors.

Table 8 presents estimation results from Equation (4). In Panels A and B, respectively, the dependent variable is the OLS and IV estimateof the decision fatigue effect. In both panels, the estimates of β_1 are statistically significant and

[13] We obtain α_{Yj} by estimating Equation (1) seperately for each physician.

positive, and the estimates of β_2 are also statistically significant but negative in all columns. The results suggest that the relationship between medical experience and the estimated decision-fatigue effect on physician behavior is nonlinear.

Figure 4 plots the OLS estimates of physician-specific decision-fatigue effects against physician's medical experience. The dashed line in each panel depicts the fitted relationship between the decision-fatigue effect and medical experience, based on the estimates of Equation (4).[14] All panels show a hump-shaped relationship between medical experience and the estimated decision-fatigue effect: Decision fatigue exerts less influence on physicians' behavior when their medical experience is moderate rather than high or low. Our results suggest that professional experience mitigates decision-fatigue effects for young physicians, while this effect fades as the physician ages.

VI. Conclusion

Using administrative data for 250,000 ED visits, we find that decision fatigue erodes the quality of treatment provided by the physician and impairs patient outcomes. Increased decision fatigue of physicians leads to lower inpatient admission rates, fewer task orders, and shorter patient length of stay; subsequently, both patient revisit rates and mortality rates increase. Our results also show that a break in the shift and physician's medical experience could alleviate the consequences of decision fatigue. Researchers have initiated efforts to design "choice architecture" or "nudges" to improve the quality of medical decision-making (Avorn, 2018). In this regard, to reduce decision fatigue, hospitals could introduce more breaks or shorter shifts, assign serious cases to less

[14] All other covariates—dummy variables of physician gender, local graduation, and continuing medical education—are held constant at zero.

fatigued physicians, and delegate certain decisions to support systems and subordinates.

Our study has broad implications for public debate on regulations for healthcare professionals. Though strict occupational licensing may ensure the quality of physicians, it also contributes to staffing shortages in the healthcare industry that cause excessive workloads for physicians (Darzi and Evans, 2016). Setting a high benchmark for qualifying physicians may have the unintended consequence of increasing the likelihood of physician shortages, greater fatigue, and degraded quality of treatment. We suggest that there is a quid pro quo incurred by demanding higher qualifications and fewer healthcare professionals. Policy makers must consider this tradeoff in light of our findings on the salient features of physician fatigue that could result in degraded medical decision-making (Friedman, 2009).

REFERENCES

Augenblick, Ned, and Scott Nicholson. 2015. "Ballot Position, Choice Fatigue, and Voter Behaviour." *The Review of Economic Studies*, 83(2): 460–480.

Avorn, Jerry. 2018. "The Psychology of Clinical Decision Making—Implications for Medication Use." *The New England Journal of Medicine*, 378(8): 689–691.

Baumeister, Roy F, Ellen Bratslavsky, Mark Muraven, and Dianne M Tice. 1998. "Ego Depletion: Is the Active Self a Limited Resource?" *Journal of Personality and Social Psychology*, 74(5): 1252.

Brachet, Tanguy, Guy David, and Andrea M Drechsler. 2012. "The Effect of Shift Structure on Performance." *American Economic Journal: Applied Economics*, 4(2): 219–46.

Chan, David C. 2016. "Teamwork and Moral Hazard: Evidence from the Emergency Department." *Journal of Political Economy*, 124(3): 734–770.

Chan, David C. 2018. "The Efficiency of Slacking Off: Evidence from the Emergency Department." *Econometrica*, 86(3): 997–1030.

Chandra, Amitabh, David Cutler, and Zirui Song. 2011. "Who Ordered That? The Economics of Treatment Choices in Medical Care." *Handbook of Health Economics*, 2 397–432.

Chandra, Amitabh, and Douglas O Staiger. 2007. "Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks." *Journal of Political Economy*, 115(1): 103–140.

Chiu, I-Min, Yan-Ren Lin, Yuan-Jhen Syue, Chia-Te Kung, Kuan-Han Wu, and Chao-Jui Li. 2018. "The Influence of Crowding on Clinical Practice in The Emergency Department." *American Journal of Emergency Medicine*, 36(1): 56–60.

Clemens, Jeffrey, and Joshua D Gottlieb. 2014. "Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?" *American Economic Review*, 104(4): 1320–49.

Cohen, I Glenn, Holly Fernandez Lynch, and Christopher T Robertson. 2016. *Nudging Health: Health Law and Behavioral Economics*. Johns Hopkins University Press.

Cooper-Patrick, Lisa, Joseph J Gallo, Junius J Gonzales, Hong Thi Vu, Neil R Powe, Christine Nelson, and Daniel E Ford. 1999. "Race, Gender, and Partnership in the Patient-Physician Relationship." *JAMA*, 282(6): 583–589.

Currie, Janet, and W Bentley MacLeod. 2008. "First Do No Harm? Tort Reform and Birth Outcomes." *The Quarterly Journal of Economics*, 123(2): 795–830.

Currie, Janet, and W Bentley MacLeod. 2017. "Diagnosing Expertise: Human Capital, Decision Making, and Performance among Physicians." *Journal of Labor Economics*, 35(1): 1–43.

Danziger, Shai, Jonathan Levav, and Liora Avnaim-Pesso. 2011. "Extraneous Factors in Judicial Decisions." *Proceedings of the National Academy of Sciences*, 108(17): 6889–6892.

Darzi, Ara, and Tim Evans. 2016. "The Global Shortage of Health Workers—An Opportunity to Transform Care." *Lancet*, 388(10060): 2576–2577.

Dzau, Victor J, Darrell G Kirch, and Thomas J Nasca. 2018. "To Care Is Human—Collectively Confronting the Clinician-Burnout Crisis." *The New England Journal of Medicine*, 378(4): 312–314.

Fang, Hanming, and Qing Gong. 2017. "Detecting Potential Overbilling in Medicare Reimbursement Via Hours Worked." *The American Economic Review*, 107(2): 562–91.

Flo, Elisabeth, Ståle Pallesen, Bente Elisabeth Moen, Siri Waage, and Bjørn Bjorvatn. 2014. "Short Rest Periods Between Work Shifts Predict Sleep and Health Problems in Nurses at 1-Year Follow-Up." *Occup Environ Med*, 71(8): 555–561.

Freeman, Michael, Susan Robinson, and Stefan Scholtes. 2017. "Gatekeeping under Congestion: An Empirical Study of Referral Errors in the Emergency Department." Working Paper

Friedman, Milton. 2009. *Capitalism and Freedom*. University of Chicago Press.

Gee, Alastair. 2011. "Concerns Raised over New US Resident Physician Work Hours." *Lancet*, 378(9793): 758.

Hallowell, EM. 2005. "Overloaded Circuits: Why Smart People Underperform." *Harvard Business Review*, 11(3): 289–299.

Hirshleifer, David, Yaron Levi, Ben Lourie, and Siew Hong Teoh. 2019. "Decision Fatigue and Heuristic Analyst Forecasts." *Journal of Financial Economics*.

Kahneman, Daniel. 2011. *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux.

KC, Diwas Singh. 2014. "Does Multitasking Improve Performance? Evidence from the Emergency Department." *Manufacturing & Service Operations*

Management, 16(2): 168–183.

Levav, Jonathan, Mark Heitmann, Andreas Herrmann, and Sheena S Iyengar. 2010. “Order in Product Customization Decisions: Evidence from Field Experiments.” *Journal of Political Economy*, 118(2): 274–299.

Li, Jing, William H Dow, and Shachar Kariv. 2017. “Social Preferences of Future Physicians.” *Proceedings of the National Academy of Sciences*, 114(48): E10291–E10300.

Linder, Jeffrey A, Jason N Doctor, Mark W Friedberg, Harry Reyes Nieva, Caroline Birks, Daniella Meeker, and Craig R Fox. 2014. “Time of Day and the Decision to Prescribe Antibiotics.” *JAMA Internal Medicine*, 174(12): 2029–2031.

List, John A., 2003. “Does Market Experience Eliminate Market Anomalies?” *The Quarterly Journal of Economics*, 118(1): 41–71.

Mani, Anandi, Sendhil Mullainathan, Eldar Shafir, and Jiaying Zhao. 2013. “Poverty Impedes Cognitive Function.” *Science*, 341(6149): 976–980.

Michtalik, Henry J, Hsin-Chieh Yeh, Peter J Pronovost, and Daniel J Brotman. 2013. “Impact of Attending Physician Workload on Patient Care: A Survey of Hospitalists.” *JAMA Internal Medicine*, 173(5): 375–377.

Morrow, Gill, Bryan Burford, Madeline Carter, and Jan Illing. 2014. “Have Restricted Working Hours Reduced Junior Doctors’ Experience of Fatigue? A Focus Group and Telephone Interview Study.” *BMJ*, 4(3): e004222.

Mullainathan, Sendhil and Eldar Shafir. 2013. *Scarcity: Why Having Too Little Means So Much*, Macmillan.

Philibert, Ingrid, Paul Friedmann, William T Williams et al. 2002. “New Requirements for Resident Duty Hours.” *JAMA*, 288(9): 1112–1114.

Physicians Foundation. 2016. A Survey of America’s Physicians: Practice Patterns and Perspectives. *The Physicians Foundation*.

Shah, Anuj K, Sendhil Mullainathan, and Eldar Shafir. 2012. “Some

Consequences of Having Too Little." *Science*, 338(6107): 682–685.

Sievertsen, Hans Henrik, Francesca Gino, and Marco Piovesan. 2016. "Cognitive Fatigue Influences Students' Performance on Standardized Tests." *Proceedings of the National Academy of Sciences*, 113(10): 2621–2624.

Wakker, Peter P. 2008. "Lessons Learned By (From?) An Economist Working in Medical Decision Making." *Medical Decision Making*, 28(5): 690–698.

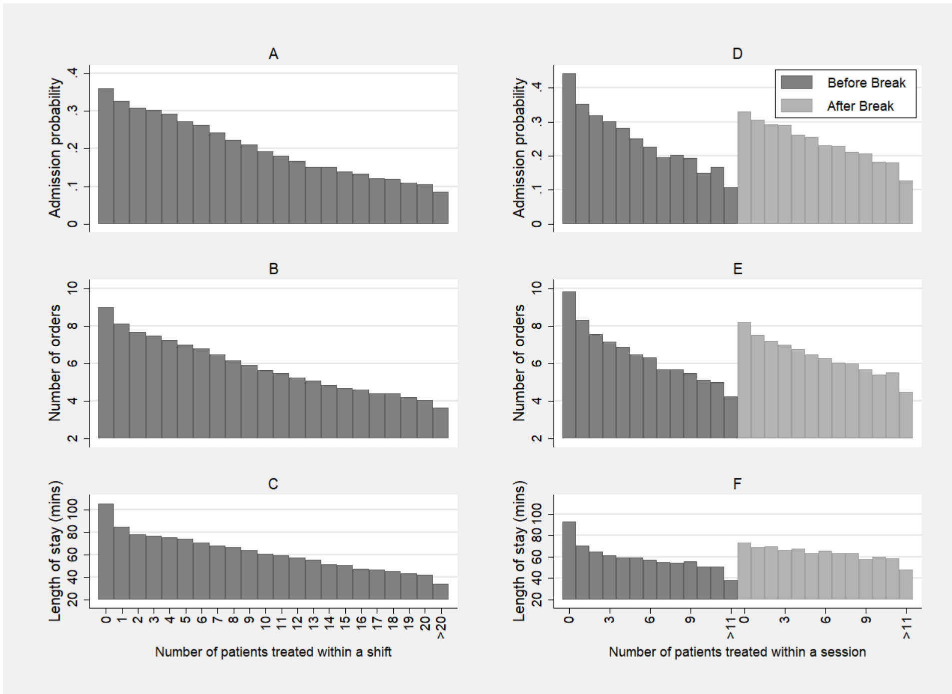

FIGURE 1. PHYSICIAN DECISIONS BY NUMBER OF PATIENTS TREATED WITHIN A SHIFT OR A SESSION

Notes: In these panels, the y-axis plots the mean values of three measures of physician decisions for the index patient: proportion of inpatient admissions, number of task orders, and patient length of stay (in minutes). In Panels A-C, the x-axis represents the number of patients physicians have seen previously during the same shift. In Panels D-E, the x-axis shows the number of patients physicians have seen previously during each of the two sessions divided by a break. Here a break is defined as a period of at least 30 minutes, during which the physician on shift is not in charge of any patient. Panels D-E only include shifts with one break.

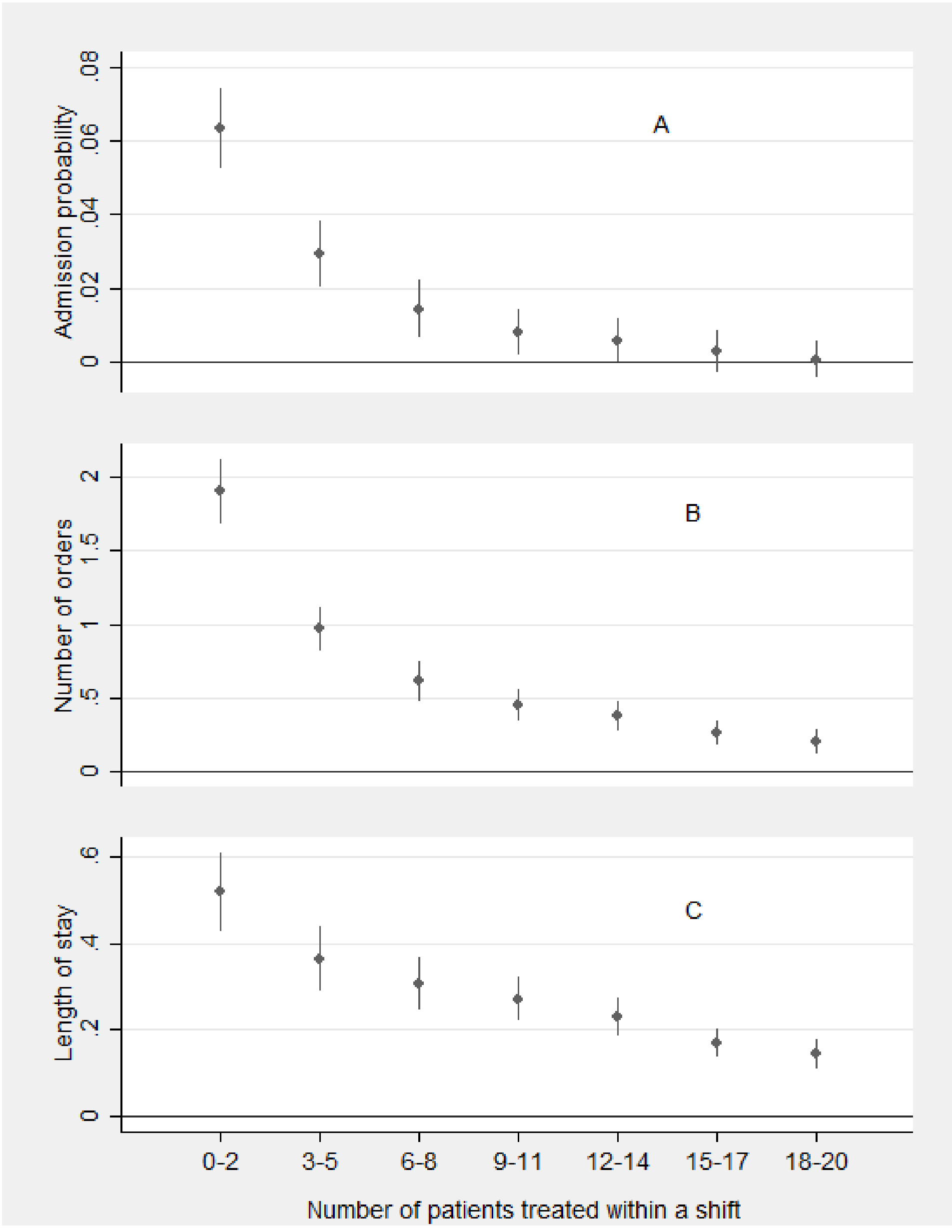

FIGURE 2. HETEROGENEOUS ANALYSIS—NONLINEAR DECISION-FATIGUE EFFECTS

Notes: This figure plots coefficients from Equation (3) estimated separately for inpatient admission (Panel A), number of task orders (Panel B), and (log) length of stay (Panel C). The reference category includes patient visits whose consultation starts when the physician has treated more than 20 patients during the shift. Dots represent point estimates from regression models, and solid bars represent the 95% confidence interval for each estimate. Results are also presented in Table 6.

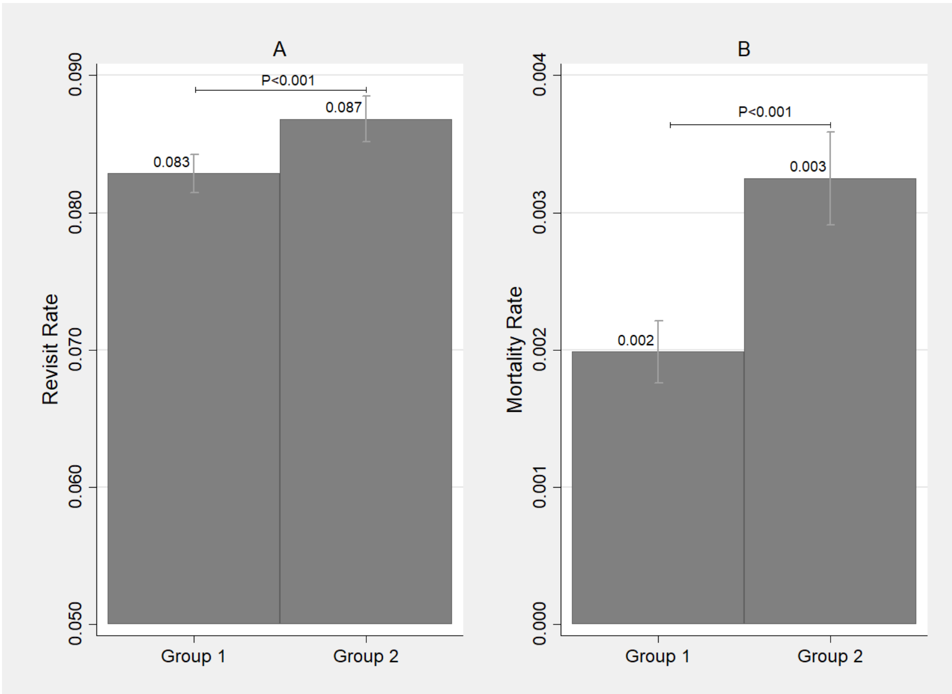

FIGURE 3. PATIENT TREATMENT OUTCOMES BY ORDINAL POSITION

Notes: Patients are stratified into two groups by their ordinal position in the shift. Group 1 comprises patients who were treated in the first half of a shift, and Group 2 the remaining patients. We compare the two groups in terms of the rates of ED revisits within 1 week in Panel A and the rates of ED mortality in Panel B. Error bars represent 95% CI. The p values reported above the top horizontal bars are from chi-squared tests of differences in means between Groups 1 and 2.

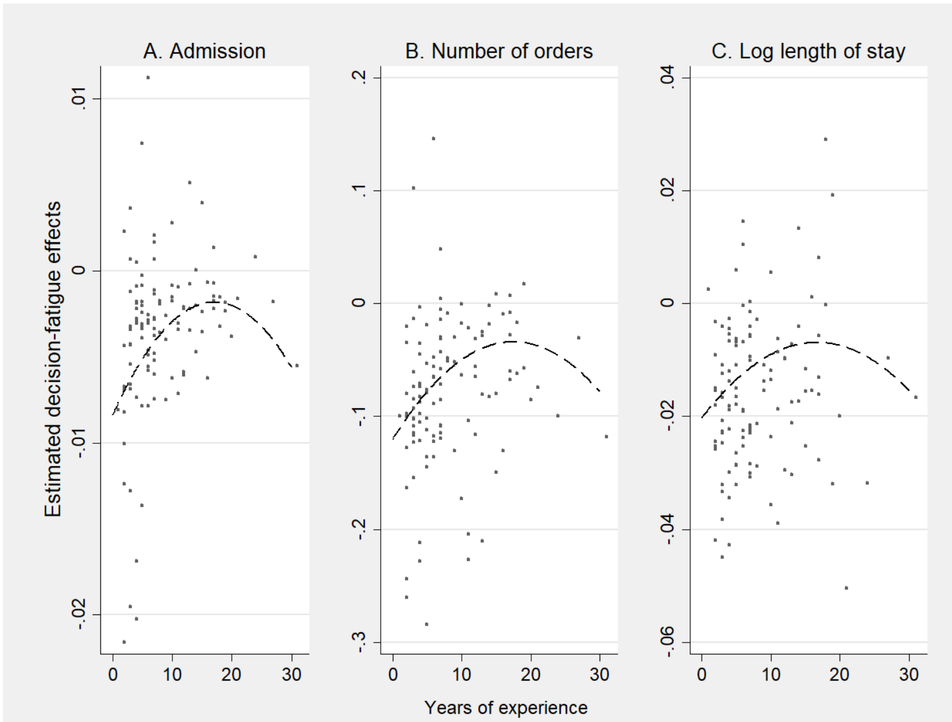

FIGURE 4. EFFECTS OF DECISION FATIGUE BY PHYSICIAN'S EXPERIENCE

Notes: This figure plots OLS estimates of physician-specific decision fatigue effect on the probability of inpatient admission (Panel A), number of task orders (Panel B), and log length of stay (Panel C) against physician's medical experience (years). Each dot represents a physician in the sample. Dashed lines depict fitted relationships between decision-fatigue effect and medical experience based on the estimates of Equation (4), holding all other covariates (dummy variables of physician gender, local graduation, and continuing medical education) constant at zero. Estimated coefficients are presented in Panel A of Table 8.

TABLE 1—SUMMARY STATISTICS

Variable	Observations	Mean	SD
Panel A: Physician decision fatigue			
Number of patients treated [a]	254,320	10.289	8.355
Panel B: Physician decisions			
Inpatient admission	254,320	0.216	0.411
Total number of orders	213,977	6.153	5.226
Patient length of stay, minutes	253,679	63.774	74.199
Panel C: Patient outcomes			
Return visits within 14 days	254,320	0.084	0.278
Death in the ED	254,320	0.003	0.050
Panel D: Patient characteristics [b]			
Male	254,320	0.647	0.478
Age	254,320	39.357	20.564
Patient severity level			
1	254,320	0.040	0.197
2	254,320	0.244	0.429
3	254,320	0.716	0.451
Panel E: Physician characteristics			
Years of experience	115	8.383	5.881
Male	115	0.791	0.408
Local graduates	115	0.539	0.501
Continuing medical education	115	0.278	0.45
Panel F: Instrumental variable			
Number of ambulance arrivals [c]	254,320	10.036	8.261

[a] *Number of patients treated by the physician from shift start to the index patient's consultation.*

[b] *Unlisted variables include patient race and diagnostic categories.*

[c] *Total number of ambulance arrivals at the ED during the physician's shift up to the index patient's consultation.*

TABLE 2— EFFECTS OF DECISION FATIGUE ON PHYSICIAN BEHAVIOR

	(1) Admission	(2) Admission	(3) Number of orders	(4) Log length of stay
Panel A	**OLS**	**Probit** [a]	**OLS**	**OLS**
# Patients treated	-0.0023***	-0.0029***	-0.0633***	-0.0157***
	(0.0003)	(0.0004)	(0.0053)	(0.0015)
R-squared	0.381	-	0.559	0.366
Percent effect: #Patients treated +10 [b]	10.6	13.4	10.3	15.7
Panel B: First-stage results				
#Ambulance arrivals	0.5094***	0.5094***	0.4954***	0.5102***
	(0.0225)	(0.0225)	(0.0214)	(0.0225)
R-squared	0.629	0.629	0.623	0.629
Panel C: IV regressions				
# Patients treated	-0.0032***	-0.0033***	-0.0939***	-0.0196***
	(0.0004)	(0.0005)	(0.0076)	(0.0019)
R-squared	0.380	-	0.558	0.366
Percent effect: #Patients treated +10 [b]	14.8	15.3	15.3	19.6
p value of Hausman test	<0.001	0.009	<0.001	<0.001
Patient characteristics	ALL	ALL	ALL	ALL
Physician FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	254,320	254,320	213,977	253,679
Sample mean outcome	0.216	0.216	6.152	3.484

Notes: Physician decision fatigue is measured by the number of patients treated before an index patient's consultation. Panel A reports OLS/probit estimates. Panel B reports first-stage estimates over the sample used in the IV regressions in Panel C. Panel C reports IV estimates, in which the instrumental variable is the number of ambulance arrivals at the ED during the physician's shift up to the index patient's consultation. Dependent variables are a dummy variable that equals one if the patient is admitted for inpatient care and zero otherwise (Column (1) and (2)), total number of task orders (Column (3)), and patient length of stay in logarithmic form (Column (4)). All regressions control for patient demographic characteristics (indicators for gender, race, and nine age categories), triage severity levels, diagnostic categories, physician fixed effects, and time fixed effects (hour of day, day of week, and month-year interactions). Standard errors in parentheses are clustered at the physician level.

[a] *Panels A and C in Column (2) report average marginal effects from the probit model.*

[b] *Percentage changes in the dependent variable relative to the mean, when the number of previously treated patients increases by 10 units. For example, every 10 patients the physician has previously treated during a shift reduces the index patient's inpatient admission probability by 2.3 percentage points, which translates into a 10.6% (2.3/21.6) reduction.*

**** Significant at the 1% level.*

*** Significant at the 5% level.*

** Significant at the 10% level.*

TABLE 3—BREAK WITHIN THE SHIFT

	(1)	(2)	(3)
	Admission	Number of orders	Log length of stay
Group 1 (α1)	0.0025	0.1844**	0.3215***
	(0.0061)	(0.0819)	(0.0222)
Group 3 (α2)	0.0133**	0.2689***	0.3019***
	(0.0053)	(0.0694)	(0.0191)
α1+α2	0.0158	0.4533	0.6234
p value of Wald test	0.093	<0.001	<0.001
Patient characteristics	ALL	ALL	ALL
Physician FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	26,258	22,912	26,109
R-squared	0.397	0.549	0.407
Sample mean outcome	0.290	7.377	3.502

Notes: This table reports coefficient estimates from OLS regressions using Equation (2). Based on administrative data, we extract shifts with a break during which the physician is not in charge of any patient for 30 minutes or more. We focus on three groups of patient visits in the extracted shifts. Group 1 refers to the last fourth to sixth visits before the break, Group 2 to the last three visits before the break, and Group 3 to the first three visits after the break. Group 2 is used as the omitted group in the regression, Outcome variables and controls are the same as in Table 2. Standard errors in parentheses are clustered at the physician level.

**** Significant at the 1% level.*

*** Significant at the 5% level.*

** Significant at the 10% level.*

TABLE 4—ROBUSTNESS ANALYSES

	(1) Admission	(2) Number of orders	(3) Log length of stay
Panel A: control for cumulative time elapsed in the shift			
# Patients treated	-0.0016***	-0.0385***	-0.0104***
	(0.0002)	(0.0052)	(0.0017)
Panel B: control for physician levels of multitasking			
# Patients treated	-0.0023***	-0.0636***	-0.0161***
	(0.0003)	(0.0057)	(0.0015)
Panel C: exclude the last three visits in each shift			
# Patients treated	-0.0027***	-0.0601***	-0.0122***
	(0.0003)	(0.0058)	(0.0016)
Panel D: control for ED patients-in-waiting			
# Patients treated	-0.0023***	-0.0628***	-0.0160***
	(0.0003)	(0.0053)	(0.0015)
Panel E: control for ED adjusted system load			
# Patients treated	-0.0023***	-0.0626***	-0.0162***
	(0.0003)	(0.0053)	(0.0015)
Panel F: current severe visits only			
# Patients treated	-0.0032***	-0.1244***	-0.0140***
	(0.0007)	(0.0214)	(0.0053)
Panel G: current nonsevere visits only			
# Patients treated	-0.0024***	-0.0545***	-0.0171***
	(0.0002)	(0.0047)	(0.0014)
Panel H: restrictions on physician shift length (6-12 hours)			
# Patients treated	-0.0020***	-0.0573***	-0.0164***
	(0.0002)	(0.0052)	(0.0014)
Panel I: restrictions on physician shift length (8-10 hours)			
# Patients treated	-0.0025***	-0.0696***	-0.0189***
	(0.0002)	(0.0047)	(0.0014)

Notes: This table reports coefficients from OLS regressions using Equation (1). Panel A adds the number of hours elapsed in the given shift as a control variable. Panel B controls for the physician's degree of multitasking, measured by the number of overlapping cases. Panel C excludes the last three visits in each shift. Panel D controls for the total number of patients waiting to be seen in the ED. Panel E controls for physician adjusted value of system load, defined as the ED system load divided by the total number of physicians on staff during the index patient's consultation. ED system load measures the total number of patients in the ED, including those waiting to be seen and those being treated. Panel F regresses on a sample of severe visits. Panel G uses a sample of nonsevere visits. Panels H and I restrict shift length to between 6 and 12 hours, and between 8 and 10 hours, respectively. Outcome variables and other control variables are the same as in Table 2. Standard errors in parentheses are clustered at the physician level.

**** Significant at the 1% level.*

*** Significant at the 5% level.*

** Significant at the 10% level.*

TABLE 5—HETEROGENEOUS ANALYSES

	(1)	(2)	(3)
	Admission	Number of orders	Log length of stay
Panel A: number of severe cases previously treated			
#Patients treated	-0.0021***	-0.0552***	-0.0153***
	(0.0003)	(0.0055)	(0.0014)
#Severe cases treated	-0.0029***	-0.1008***	-0.0062
	(0.0010)	(0.0185)	(0.0065)
Panel B: time off between shifts			
#Patients treated	-0.0023***	-0.0614***	-0.0161***
	(0.0002)	(0.0054)	(0.0014)
#Patients treated* Quick return	-0.0011**	-0.0338***	-0.0002
	(0.0004)	(0.0063)	(0.0014)
Panel C: patient-physician race and gender concordance			
#Patients treated	-0.0025***	-0.0717***	-0.0155***
	(0.0003)	(0.0065)	(0.0023)
#Patients treated*Race-Concordance	-0.0002	0.0102***	0.0007
	(0.0002)	(0.0029)	(0.0012)
#Patients treated*Gender-Concordance	0.0004*	0.0074**	-0.0009
	(0.0002)	(0.0030)	(0.0020)

Notes: This table reports coefficients from OLS regressions using Equation (1). Panel A adds the number of severe cases treated as an independent variable. Quick return in Panel B indicates whether the physician takes less than 11 hours off after the previous work shift. Panel B includes the quick return indicator and the interaction term between the quick return indicator and the number of previously treated patients in the current shift. Panel C includes patient-physician race and gender concordance status and interacts the number of patients treated with race (gender) concordance, where Race-Concordance (Gender-Concordance) is an indicator whether the index patient has the same race (gender) as the physician. Outcome variables and other control variables are the same as in Table 2. Standard errors in parentheses are clustered at the physician level.

**** Significant at the 1% level.*

*** Significant at the 5% level.*

** Significant at the 10% level.*

TABLE 6—NONLINEAR DECISION-FATIGUE EFFECTS

	(1)	(2)	(3)
	Admission	Number of orders	Log length of stay
# Patients treated:			
0-2	0.0798***	2.0559***	0.4671***
	(0.0067)	(0.1096)	(0.0396)
3-5	0.0410***	1.0645***	0.2877***
	(0.0058)	(0.0772)	(0.0318)
6-8	0.0212***	0.6563***	0.2307***
	(0.0045)	(0.0629)	(0.0258)
9-11	0.0103***	0.4264***	0.2061***
	(0.0035)	(0.0534)	(0.0194)
12-14	0.0065**	0.3722***	0.1834***
	(0.0028)	(0.0455)	(0.0161)
15-17	0.0070**	0.2551***	0.1286***
	(0.0032)	(0.0356)	(0.0129)
18-20	0.0022	0.2014***	0.1007***
	(0.0027)	(0.0380)	(0.0118)
Patient characteristics	ALL	ALL	ALL
Physician FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	254,320	213,977	253,679
R-squared	0.382	0.563	0.366
Sample mean outcome	0.216	6.152	3.484

Notes: This table reports coefficients from OLS regressions using Equation (3). Results are graphically shown in Figure 2. Outcome variables and controls are the same as in Table 2. Standard errors in parentheses are clustered at the physician level.

**** Significant at the 1% level.*

*** Significant at the 5% level.*

** Significant at the 10% level.*

TABLE 7—PHYSICIAN DECISION FATIGUE ON PATIENT OUTCOMES

	(1)	(2)
	7-day revisit to the ED	Death in the ED
Panel A: OLS estimates		
# Patients treated	0.00025***	0.00004**
	(0.00009)	(0.00002)
R-squared	0.025	0.068
Percent effect: #Patients treated +10	3.0	13.3
Panel B: First stage results		
# Ambulance arrivals	0.5094***	0.5094***
	(0.0225)	(0.0225)
R-squared	0.629	0.629
Panel C: IV regressions		
# Patients treated	0.00023	0.00017***
	(0.00017)	(0.00006)
R-squared	0.025	0.068
Percent effect: #Patients treated +10	2.8	56.7
p value of Hausman test	0.907	0.004
Patient characteristics	ALL	ALL
Physician FE	YES	YES
Time FE	YES	YES
Observations	254,320	254,320
Sample mean outcome	0.084	0.003

Notes: Panel A reports OLS estimates. Panel B reports first-stage estimates over the sample used in the IV regressions in Panel C. Panel C reports IV estimates in which the instrumental variable is the number of ambulance arrivals at the ED during the physician's shift up to the index patient's consultation. Dependent variables in Columns (1) and (2) are dummy variables for 7-day revisit to the ED and death in the ED, respectively. Controls are the same as in Table 2. Standard errors in parentheses are clustered at the physician level.

**** Significant at the 1% level.*

*** Significant at the 5% level.*

** Significant at the 10% level.*

TABLE 8—CORRELATES OF DECISION-FATIGUE EFFECTS AND PHYSICIAN CHARACTERISTICS

	Estimated decision-fatigue effects on:		
	(1)	(2)	(3)
	Admission	Number of orders	Log length of stay
Panel A. OLS estimates of decision-fatigue effects			
Experience	0.00077***	0.00986***	0.00160**
	(0.00025)	(0.00363)	(0.00074)
Experience-squared	-0.00002**	-0.00028**	-0.00005*
	(0.00001)	(0.00013)	(0.00003)
R-squared	0.131	0.083	0.073
Sample mean outcome	-0.004	-0.078	-0.016
Panel B. IV estimates of decision-fatigue effects			
Experience	0.00116***	0.01353**	0.00243*
	(0.00039)	(0.00664)	(0.00129)
Experience-squared	-0.00004***	-0.00046*	-0.00010**
	(0.00001)	(0.00025)	(0.00005)
R-squared	0.135	0.043	0.055
Sample mean outcome	-0.006	-0.130	-0.026
Observations	115	115	115

Notes: Coefficients from OLS regressions using Equation (5). Outcome variables in Columns (1)-(3) represent the estimated physician-specific decision-fatigue effect on inpatient admission decision, number of orders, and log length of stay, respectively. Physician-specific decision-fatigue effect is obtained by estimating Equation (1) separately for each physician using OLS (Panel A) and IV (Panel B) estimations. All regressions control for physician gender, one dummy variable that indicates a first degree from a local medical school, and another dummy variable that indicates continuing medical education. Standard errors in parentheses are bootstrapped.

**** Significant at the 1% level.*

*** Significant at the 5% level.*

** Significant at the 10% level.*

APPENDIX

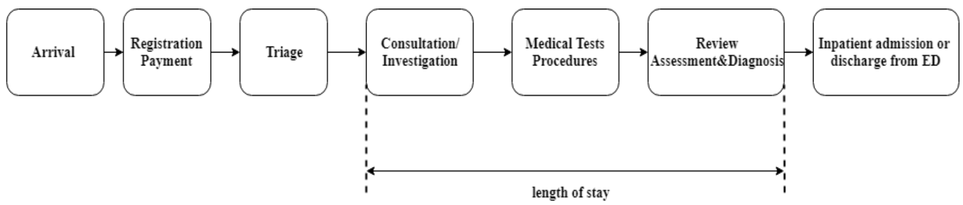

FIGURE A.1. PATIENT FLOW IN THE EMERGENCY DEPARTMENT

Notes: This figure depicts the general patient flow in the ED, starting with patient arrival and ending with the patient's being admitted to the hospital or discharged from the ED. Patient length of stay is measured from the start time of the patient's consultation to the end of the consultation. Case end is not necessarily the same as consultation end. For example, a patient's consultation ends but the patient is still waiting to be admitted; the case does not end until the patient is admitted.

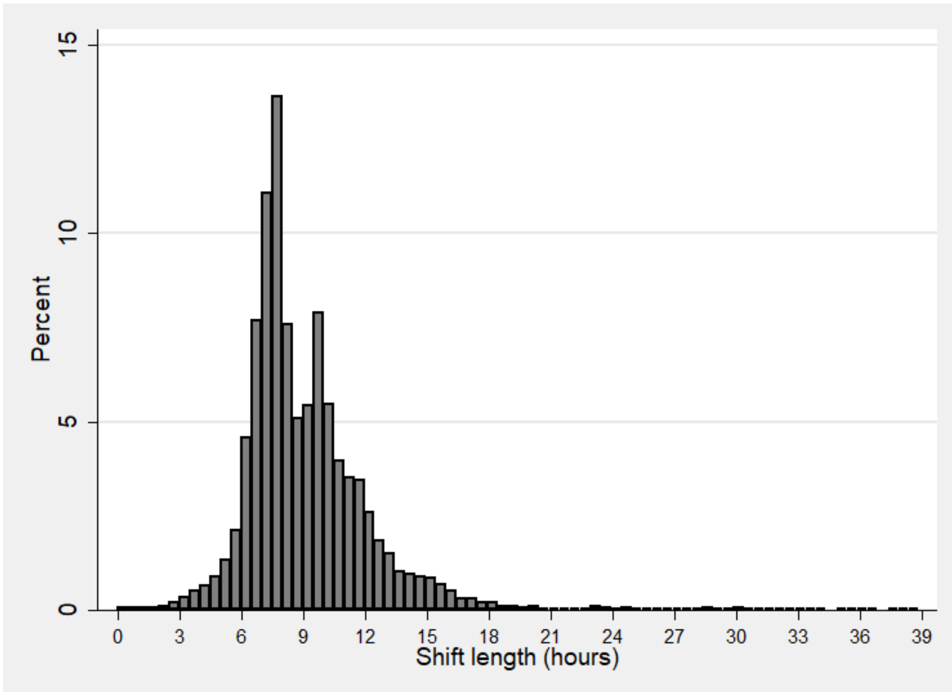

FIGURE A.2. DISTRIBUTION OF SHIFT LENGTHS

Notes: A new shift is defined to begin when a physician starts the first patient visit after 6 or more hours of inactivity. Shift length is measured as the number of hours elapsed from the start of the first visit's consultation to the end of the last consultation in the shift.

TABLE A.1—STATISTICS FOR AMBULANCE OPERATORS

Ambulance Operators	Frequency	Percent
SCDF Ambulance	32,129	93.41%
Private Ambulance	2,156	6.27%
Police Vehicle	39	0.11%
Others	73	0.21%
Total	34,397	100.00%

Notes: Data from patient visits delivered by ambulance in the main analytic sample.

TABLE A.2— EFFECTS OF DECISION FATIGUE ON PHYSICIAN BEHAVIOR

	(1)	(2)	(3)	(4)
	Admission	Admission	Number of orders	Log length of stay
Panel A	**OLS**	**Probit**	**OLS**	**OLS**
# Patients treated	-0.0024***	-0.0031***	-0.0681***	-0.0165***
	(0.0003)	(0.0004)	(0.0056)	(0.0016)
R-squared	0.357	-	0.525	0.341
Percent effect: #Patients treated +10	11.1	14.4	11.1	16.5
Panel B: First stage results				
# Ambulance arrivals	0.5098***	0.5098***	0.4958***	0.5106***
	(0.0225)	(0.0225)	(0.0214)	(0.0225)
R-squared	0.629	0.629	0.623	0.629
Panel C: IV regressions				
# Patients treated	-0.0034***	-0.0036***	-0.1007***	-0.0203***
	(0.0004)	(0.0005)	(0.0079)	(0.0020)
R-squared	0.357	-	0.524	0.341
Percent effect: #Patients treated +10	15.7	16.7	16.4	20.3
p value of Hausman test	<0.001	0.005	<0.001	<0.001
Patient characteristics	Ex ante	Ex ante	Ex ante	Ex ante
Physician FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	254,320	254,320	213,977	253,679
Sample mean outcome	0.216	0.216	6.152	3.484

Notes: This table reestimates the results in Table 2 using a different set of controls for patient characteristics. Patient characteristics here include only ex ante characteristics of demographics (gender, race, and age group) and triage severity index. Dependent variables and other control variables are the same as in Table 2.